Data analytics and health services quality: Implementing eHealth initiatives wisely

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Introduction

Data has become an increasingly valuable organisational resource, as big data analytics allow organisations to analyse ever larger and disparate digitised data sets (OECD 2015:20; Ross et al. 2017:114-119). These strategies in turn facilitate data driven and/or supported decision making practices (Almeida et al. 2015; Baum et al. 2014; Pedersen & Aagaard 2015; Pedersen and Wilkinson 2018; Ross et al. 2017). ‘eHealth systems’ are likewise being linked to ever more sophisticated data banks and statistical analysis (Holroyd-Leduc et al. 2011; Pedersen & Aagaard 2015; Poucke et al. 2016). Proponents of eHealth systems suggest that such strategies can improve health care structures and processes, which in turn improve patient outcomes, (Holroyd-Leduc et al. 2011; McMorrow, Kenney, & Goin, 2014; Smith et al. 2011). This includes the ability to provide better ‘evidence based’ decision making based on the results of analysed data (Ross et al. 120-121).

Critics, however, suggest that eHealth systems can lead to data driven management (DDM) systems that create top down decision-making data driven bureaucracies, that reduce front line services, autonomy and discretion and undermine professional expertise (Pedersen & Aagaard 2015). This in turn may negatively impact on staff adoption of new DDM procedures (Ross 2015). Implementation approaches and strategies therefore impact on eHealth outcomes, including the system’s perceived usefulness and staff acceptance (Holroyd-Leduc et al., 2011; Ross 2015; Ross et al. 2107). Rising health costs and finite health budgets, further begs the question of whether eHealth metrics are being used to deliver more ‘efficient results’, in terms of costs, or more ‘effective patient outcomes’, in terms of overall patient well-being? These two outcomes of course do not need to be mutually exclusive, however, it does suggest the need for a closer examination of the goals and aims of eHealth-related strategies and their outcomes (see also Black et al., 2011).

The following two questions then helped to guide the research that underpins this chapter. First, what does the literature suggest have been the main drivers of data analytic-supported eHealth systems across industrialised economies and what associated implementation

challenges do eHealth systems raise? This includes identifying supportive contexts and considering the appropriateness of the mechanisms of these workplace changes (see Nancarrow et al. 2013). Second, how are data analytic-supported eHealth systems impacting on the quality of health services, including in the Australian context? It is appropriate to note here that the Australian hospital system has public and private sectors, with some private hospitals run as not-for-profit, some for-profit, and with some private entities securing tenders to operate public hospitals. The funding arrangement between the states and the Commonwealth government is complex and at times fraught. Financial resources comprise a mix of funding from government, health insurers, and patients. However, each hospital operates as a discrete entity with its own organisational and management structure. (Wilkinson et al 2018)

The chapter approaches these two questions by first systematically reviewing the literature to synthesise emerging themes in eHealth's evolution and development across the OECD group of countries. The examination of the literature is further supported by the authors' research and knowledge of the health sector. The chapter then analyses a case study based on an Australian eHealth initiative, entitled, 'Choosing Wisely Pathology', which provides evidence and grounds for conjecture in relation to factors that may underlie the successful implementation of data-analytic supported eHealth projects. We conclude by considering the types of practices and policies that are more (or less!) likely to support successful eHealth initiatives.

Research methods

Systematic literature reviews of healthcare services research (HSR) have the capacity to provide new knowledge that can in turn guide policy development, implementation and innovation across the sector (Black et al. 2011). The rationale of the following literature review is to identify emerging themes through a systematic literature review of published eHealth studies. In order to minimise variations in national contexts, only studies from OECD countries with similar healthcare systems were included.

English language peer reviewed full-text journal articles published during 1996-2017, were initially searched in the electronic databases of Medline, ProQuest, CINAHL, Informit, and Cochrane Library to identify literature suitable for inclusion in this study. The search criteria included the key words electronic medical records (EMR), electronic health records (EHR), Australia, health outcomes and big data analytics. Following the screening of the initial search

results, the search period then focused on the years 2011-2016, as an examination of the data ascertained that this time period reflected a rapid growth in OECD country implementation rates of eHealth systems and services (Pearce, and Bainbridge, 2014).

A total of 987 articles were screened and 71 articles were assessed for eligibility. Of these 48 articles were excluded as they were not relevant to this study (exclusions were by time period and relevance to the Australian health system). Seven more articles were discovered from the review of the references, producing a total of 30 studies for a systematic review. The literature review further uses supporting literature and reports to assist in the analysis of the above articles.

Figure 1: eHealth model – Key Elements

The Donabedian framework, outlined in Figure 1, was used to assist in analysing the material, including an examination of 'implementation strategies', 'adoption rates' and reported 'outcomes' outlined in the literature and the case (see Figure 1). The analysis of the articles in conjunction with other relevant literature also resulted in the identification of 15 historical eHealth themes, which are summarised in Appendix 1.

A case study then provides an interesting segue to the literature review by providing a real life example of the implementation, adoption and outcomes of a data analytic-supported eHealth initiative in the Queensland health sector. Entitled "Choosing Wisely Pathology", this project

sought to develop more effective approaches to pathology testing in a large Australian public hospital.

The case study further allows the authors to apply many of the themes, theories and frameworks identified in the above literature review to the case analysis and discussion.

eHealth

eHealth systems, based on electronic health records (EHR) and/or electronic medical record (EMR) data, were first adopted across the (OECD) countries, including Australia, in the early 1990s (Holroyd-Leduc, Lorenzetti, Straus, Sykes, & Quan, 2011). The emergence of standardised information and communication technology (ICT) –supported healthcare systems across Europe for the healthcare services sector further supported these developments (Hovenga, Kidd, & Cesnik, 1996). In line with this OECD trend the first IT/14 Committee of Standards Australia was set up in 1991 to facilitate the development of health informatics.

eHealth systems introduced more than just structural changes, as they led to new processes and outcomes in health services (Holroyd-Leduc et al., 2011). The interactions of three critical service framework elements; structure, processes and outcomes then impacted on healthcare quality (Atkins, Kilbourne, and Shulkin 2017). Despite these changes, actual improvements in health outcomes sometimes remained unclear (Zwicker, Seitz, and Wickramasinghe 2014). Researchers, for example, suggest that the potential goals of eHealth systems in terms of effective policy and practice have not always been clearly defined, while eHealth adoption and implementation have not been consistent across the OECD countries (Popay et al. 1998; Tierney et al. 2016). Researchers further suggest that healthcare quality outcomes have not always correlated with the forecasted results of the eHealth models (Zwicker et. al. 2014), while empirical evidence on what these new systems are actually achieving is inconclusive (Black et al, 2011).

Our review therefore examines eHealth services research findings in order to better understand the emergence and utilisation of these systems and associated health data analytics. The review is divided into a number themes that recurred in the literature, that further link to aspects of the implementation, adoption and reported outcomes of eHealth strategies.

Disparate stakeholder groups

The effective diffusion of eHealth systems has been challenged by the marked differences in the opinions and goals of the different healthcare services stakeholders. Historically this ‘subjectivity issue’ was identified as a major concern in eHealth implementation (Popay et al. 1998). Clinicians, ICT services, customers, carers, auxiliary staff, administrators, and Government agencies, for example, often have different perspectives on eHealth goals, processes and outcomes. Health service staff further tend to work in ‘silos’ of work cultures, with the divide between clinicians and administrative staff being a well-known example (Kilbourne et al. 2010). Smith et al. (2011) likewise comment that the successful implementation of eHealth strategies requires collaboration between management, ICT staff and clinicians. Differing stakeholder perspectives then require a multitude of standards and criteria to be synthesised and combined in order to develop eHealth standards. Health services have therefore found eHealth systems to be a complex construct to develop and implement (Black, et al., 2011). Reports further suggest that the implementation of earlier eHealth systems was often disjointed, with mixed results (Lieu, & Cho, 2011; McGinn et al. 2012).

Despite the rapid advances being made in the ICT sector, disparate stakeholder goals and objectives in part led to the often ‘reluctant adoption’ of these technologies across the healthcare system in the new millennium (Ford et al. 2006). Stakeholders, for example, were sceptical in terms of claimed outcomes, time frames were deemed unachievable and outcome metrics were not universally accepted (Ford et al. 2006, Menachemi, & Phillips, 2006). Some of this scepticism was caused by the juxtaposition of lay knowledge and professional knowledge between healthcare services stakeholders. Ford et al. (2006) recounts the challenges of implementing eHealth systems in small medical offices (with less than ten physicians in one office) due to perceptual differences between policy makers and physicians. Perhaps not surprisingly, the clinicians focussed on health outcomes, the ICT personnel focused on the ICT infrastructure and the government policy makers focused on costs. Ford et al., (2006) therefore advise that the evolution of eHealth services requires participatory designs involving all stakeholders and public. This suggests the need for collaborative implementation strategies to overcome disconnections between stakeholder groups, such as, consensus-based quality frameworks (Kilbourne, Fullerton, Dausey, Pincus, & Hermann, 2010).

Knight et al. (2014) similarly discuss the potential benefits of collaborative approaches to eHealth. Their research examined a ‘quality problem’ in the context of implementing personally controlled electronic health records in primary care systems in Australia. This

problem occurred in part because the quality indicators and data quality definition measures that were developed and introduced were not collaboratively defined in terms of ‘outcomes’. This led to the introduction of a collaborative stakeholder program that aimed to improve the quality of the eHealth data. This included the introduction of Collaborative Program Managers (CPMs) and the involvement of ‘patients as partners’ (Knight et al. 2014:412: 416). Interestingly they found that many patients were enthusiastic about being actively involved in the program (Knight et al. 2014:416). This included patients ‘checking and improving the accuracy of their own clinical data’ and providing ideas and suggestions that allowed clinicians to better consider how electronic health data processes could be improved from a layperson’s perspective (Knight et al. 2014:416).

The effective implementation of data analytics in health sectors may also be constrained by the reluctance of different stakeholders to ‘share’ data (Roberson et al. 2016). While the very nature of the healthcare creates valid privacy concerns, the term ‘data hugging’ has been coined to explain ‘overly cautious approaches to data sharing’ that are often found across the sector (Roberson et al. 2016:593). Overcoming data hugging issues, such as patient privacy, and effectively ‘sharing’ health information between providers, support staff, allied health workers and all patients may therefore be a critical underlying factor in the successful implementation of eHealth systems.

Daniels similarly advises that ‘Historically, Australian doctors and nurses faced vast challenges from systems that didn’t communicate with each other’ (cited by Dinham 2018). Atkins et al. (2017) further point out that differing local health sector contexts may impact on structures and processes and therefore lead to different eHealth quality outcomes in different areas or regions (Atkins, Kilbourne & Shulkin 2017). Disparate stakeholder cohorts allied to differing local contexts and multiple ICT systems, therefore means that eHealth ‘solutions’ need to consider large sets of comprehensively defined key variables of cross-discipline origin, that often have complex relationships with each other. This in turn further reinforces the need for collaborative eHealth implementation approaches across the different stakeholder groups.

Psychological Ownership

Any claimed gains associated with the introduction of new ICT systems, will not occur ‘if the individual users do not accept these systems for task performance in the first place!’ (Bhattacharjee & Sanford 2006:805). Organisations must therefore ensure worker

‘acceptance’ of new ICT systems. This may not be an easy task, as workers are often sceptical about how new systems will be an improvement on existing processes and the underlying goals of management in relation to the roll out of new technologies. For example, is this more about cost cutting and/or work intensification? (Ross 2015). This in turn may lead to passive resistance to the use of the new technologies, while there are also ‘opportunity costs’ associated with learning new technologies in terms of the time it takes a worker to learn new processes and systems (Ross 2015).

In this regard, a study by Paré et al. (2006) found that the construct, ‘psychological ownership’ significantly impacted on the willingness of physicians to adopt ICT supported systems in the Health sector. Psychological ownership in this context depended on two perceived key factors, ‘usefulness’ and ‘ease of use’ (see also Bhattacharjee & Sanford 2006; Venkatesh et al. 2003). Research on the adoption of new technologies by staff in the university sector further found evidence that workers self-selected those workplace technologies that they were required to use, saw value in using and that would provide better support or assistance than existing technologies and processes (Ross 2015:17). This again supports the perceived usefulness and ease of use concepts outlined above.

Karahanna et al. argue that perceptions of usefulness are shaped by a user’s existing knowledge of structures, processes and outcomes values (2006). These perceptions will further be moderated by the user’s personal values (Karahanna et al. 2006). This suggests that clinicians are likely to be cautious in their initial adoption of any new disruptive technology, such as eHealth, as they would want to ensure that its safety and efficacy did not breach existing norms, minimum requirements and individual values (Paré et al. 2006). The new technology or intervention must therefore first prove its efficacy and usefulness through empirical demonstration (Black et al. 2011). ‘Participatory eHealth development’ has therefore been shown to have a positive influence on the psychological ownership of new intervention programs amongst clinicians (Wentzel et al. 2014), as it allows them to discover the programs’ proposed benefits through implementation. This then improves the clinicians perceptions of the eHealth system’s usefulness and rates of adoption should increase (conversely, adoption rates will decrease if this is not the case!).

While training is obviously an important component in promoting the use of new eHealth systems, Pare et al. (2006) further suggests that perceptions concerning the second key factor

in psychological ownership, ease of use of use, are also highly dependent on a user's 'initial' experience of a new system. Put simply, if the users find the new system difficult to use in the initial stages, then they are less likely to use and/or persevere with it in the longer-term. Most readers would probably agree that the triumph of technology over practical application is not an uncommon experience in 21st century workplaces! (Ross 2011; Ross & Blumenstein 2013). Generic 'bolted on' software, can be a particular bugbear in this regard, as it may not be designed with local contexts in mind.

Designing eHealth system interfaces in consultation with end users, in contrast, leads to higher system adoption rates, as the system can then be designed in a way that works for the people that actually have to use it (Wentzel et al. 2014). Ongoing success in relation to implementation and adoption is therefore determined by the reinforcement of initially positive user perceptions. It further highlights the need for collaborative approaches in eHealth design, from initial to implementation stages (Knight et al., 2014; Wentzel et al., 2014), while subsequent user feedback may then support ongoing quality improvements.

The normalisation of eHealth

The increasing implementation and adoption of eHealth technologies through the first decade of the new millennium led to new eHealth supported processes and structures that in turn were changing clinical practices (Mechanic, 2008). Models of care (MoC), for example, changed to accommodate these new technologies, while a new generation of health sector workers began seeing eHealth adoption as a sign of increased professionalism (Mechanic, 2008). eHealth systems in this changing contest then became increasingly normalised, rather than novel, as clinicians started integrating these technologies more routinely into their work. This was supported by a growing acceptance of the inevitability of ICT-supported systems playing a greater role, from both clinical and administrative perspectives (Mechanic 2008). Costing metrics and Six-Sigma type quality assurance measures were similarly introduced into health sector workplaces around this time (Zwicker, Seitz, & Wickramasinghe, 2014).

Australia is known for being an early technology adopter and interestingly by the mid-2000s the Australian health system was considered to be more mature in terms of eHealth implementation than the USA (Ford, Menachemi, & Phillips, 2006). These developments led to the establishment of the Australian National Electronic Health Transition Authority (NEHTA) in 2005, which coordinated and lead eHealth adoption across the country. In 2016

the activities of the NEHTA were then transferred to a new Australian Digital Health Agency (ADHA) (AIHW 2016).

Perhaps not surprisingly, Boruff and Bilodeau also found that millennials entering the workforce have had a dramatic effect on the adoption of eHealth technology (2012). This included medical students using smart mobile devices to access library resources and other information (Boruff & Bilodeau, 2012). Physicians have also found the use of mobile devices for eHealth attractive due to their accessibility and utility (see Paré et al. 2006). While patient self-diagnosis using ‘Dr Google’ is a two edged sword, the above research suggests that data-analytic supported diagnoses will continue to play a greater role in health care.

This includes eHealth systems being linked to personal wearable technologies that monitor the health of the individuals outside of the hospitals (Free et al. 2010). The integration of health data between clinical information systems (CIS) and personal devices then takes eHealth into the public domain. Free et al., (2010) use the term m-health in relation to the changes that are occurring in the structure and processes of existing healthcare services through the use of mobile technologies. Their systemic review of the literature concluded that m-Health type monitoring had the potential to improve health outcomes in clinical areas, such as “diagnosis, investigation, treatment, monitoring, treatment compliance and disease management; and health related processes, such as, health promotion, managing appointments, result notification and vaccination reminders” (Free et al. 2010; see also Wolin et al., 2015).

The integration of eHealth with emerging m-Health solutions further has the potential to expand the outreach of these services to remote areas. Rapid ICT advances coupled with increasingly ubiquitous smart phone and tablet access means that such changes will become increasingly commonplace, although such approaches need to overcome the digital divide in relation to the relative lack of digital access for some socio-economic groups and regional/remote areas (Baum, Newman, and Biedrzycki, 2014).

Data Analytics

While the term big data has in some ways been overhyped by ICT consultants and firms alike, it has given data analytics a higher profile in relation to organisational strategies (Ross et al. 2017). Put simply, big data refers to the ability of new technologies to analyse large and disparate data sets, including in real time. Increasing amounts of digitised data, decreased data

storage and computational costs (linked to the development of distributed storage and cloud-computing technologies) and improved data analytics have supported the development of these concepts and strategies (Ross & Blumenstein 2015; Ross et al. 2017:116). Demirkan and Delen state that cloud-based big data systems are also a cost-effective means of implementing ‘decision support systems’ in service oriented organisations that reduce and/or negate the need for frequent manual reviewing of the data (2013).

The scale of the health sector, allied to the high amounts of digitised data it now generates, lends itself to big data type analytics (Demirkan, & Delen, 2013). Aggregating electronic health data and applying eHealth based data analytics at scale has therefore become commonplace in OECD countries (Zhang, Sun, Chitkushev, & Brusic, 2014). Proponents advise that eHealth data analytics can provide administrative benefits, such as, delivering health reimbursements more quickly and efficiently, along with greater allocative efficiencies, as funding models can better reflect actual cash flows in healthcare services (Zhang et al. 2014; Cogeze et al. 2015).

Hawley et al. elaborate that eHealth big data analytic systems allied to open health data, can support collaborative mechanisms across different health services that facilitate timely diagnosis and cost-effective healthcare (Hawley et al. 2014). Data analytic programs, for example, have been used to develop patient admission prediction tools for emergency departments in Australian hospitals, allowing hospitals to better match staffing levels to predicted patient numbers (Ross et al. 2017:122). Crawshaw et al. also found evidence that data analytic systems had reduced the cost of managing laparoscopic surgeries (2015). These technologies are further facilitating the development of new approaches to health care, such as Predictive, Preventive and Personalized (PPPM) Medicine (McMorrow, Kenney, & Goin, 2014; Van Poucke et al., 2014, 2016). Data analytics has therefore become a powerful change agent within eHealth.

Researchers, however, caution that eHealth operates within complex systems and as such may require ‘more nuanced analyses’ what exists with much of the generic big data literature (Kitchin, 2014, p.3). Kennedy et al. (2017) further advise that health service data analytics need to provide ‘meaningful’ services to individuals and populations, rather than simply supplying aggregated bureaucratic reports. As mentioned above, connecting and sharing databases between disjoint health sector providers, such as public facilities, GP services and

private hospitals, is also a challenge for big data analytics (Hall et al., 2012; He et al 2014). McGinn, for example, comments that there was often no sharing of eHealth data between Canadian GP offices or between GP offices and specialists, despite the technical capability to do so (2012). As such there were no integrated GP electronic health records suitable for big data analytics (McGinn 2012). Hospitals further often run myriad ICT systems within their own organisations, including legacy and newer systems, that may not be easily linked.

Mohammed et al. (2014) also discuss interoperability issues in relation to population health data. Given its sheer size, this information would appear well suited to big-data type analysis. The data contained in individual health records, however, often needs to be integrated across different health record systems before big data analytics can gain useful insights and deeper knowledge (Mohammed, Far, and Naugler 2014).

More recent evidence however suggests that these challenges are not insurmountable. In 2018, for example, two Australian hospitals were recognised as adopting the highest Healthcare Information and Management Systems Society (HIMSS) international standards in relation to their electronic medical record adoption model (Dinham 2018). Many of the stated improved outcomes related to their ability to coordinate electronic medical records across different hospital areas and clinical disciplines. This allowed clinicians quicker access to comprehensive patient medical records, which in turn supported better health outcomes, particularly for patients with complex medical conditions that crossed clinical boundaries (Dinham 2018).

These health organisations therefore appeared to be overcoming integration and coordination issues. It further supports the view that data analytics across the health sector are more effective if health record data sources are designed with interoperability in mind, as they can then be more effectively networked, processed and analysed (Erekson, and Iglesia, 2015; Nuti et al., 2014). Studies suggest that these types of eHealth initiatives also bring about ongoing dynamic benefits, including positive behavioural changes in relation to more constructive data sharing amongst health sector worker cohorts (Dahlen et al., 2014; Hawley, Jackson, Hepworth, & Wilkinson, 2014).

Despite the apparent benefits associated with better coordinating electronic medical records, the implementation of the Australian government's My Health Record policy highlights the challenges that may accompany government initiatives that seek to better link and analyse large

amounts of individual health data (ADHA 2018a; Bedo & Whigham 2018; Kwan 2018; Smee 2018). In this regard, the My Health Record policy aims to create electronic health records that link and collate individual health information for Australian citizens (ADHA 2018a), such as, linking up health information data from the various health providers that an individual may visit. This in turn allows GPs and hospitals to quickly access pertinent health data for the individual patient concerned, no matter where they are being treated (ADHA 2018a). Researchers further suggest that government funded health data, such as the My Health Record data, is a potentially valuable resource, that should be processed and published in an open way in order to achieve the best economic and social use of the data (Van Poucke et al. 2016). The My Health Records Act similarly allows for this health information to be used by ‘approved users’ for public health and research purposes (ADHA 2018b; Smee 2018). It should be noted that in order to better address privacy concerns, only de-identified data can be released without the individual’s consent (ADHA 2018b; Smee 2018).

Despite these potential benefits in terms of individual patient treatment and health sector research outcomes, the My Health Record program has elicited some controversy, including privacy and implementation concerns (Kwan 2018; Smee 2018). Health sector data by its very nature contains potentially sensitive information. Despite government assurances of strict privacy controls, some critics warned that the UK experience in implementing and subsequently abandoning a similar system, suggested that governments do not have a good track record in regards to protecting sensitive health data from leaks (Bedo & Whigham 2018). Commentators also criticised the need for Australian citizens to ‘opt out’ rather than ‘opt in’ to the proposed new system, if they did not wish to have an electronic My Health record automatically created on their behalf (ADHA 2018c; Kwan 2018; Bedo & Whigham 2018). Following a backlash and stakeholder pressure the government amended the legislation to allow Australian citizens to opt out of the system and have their data permanently deleted at any time.

Dealing with stakeholder concerns, is needed if governments are to fully deliver platforms for public use of electronic health data (Almeida, et al., 2015; Lieu, & Cho, 2011). Research in Canada and Hong Kong suggest that these types of implementation challenges and concerns may be better approached through the development of more ‘participatory models’ of eHealth, including increased collaboration between all stakeholders, including the end users of the eHealth system (Lieu, & Cho, 2011; McGinn, et al., 2012). Knight et al. similarly suggest that

“eCollaborative” methodologies, which include participation from patients and the public, also improve data measures and quality (Knight et al., 2014). Meslin and Schwartz (2015) also provide interesting research in this area, including guidelines on how electronic hospital record data may be managed without violating privacy laws.

Despite these potential implementation issues and challenges, research shows that data-analytics are increasingly impacting on organisational decision making practices (Chen et al. 2012:1158; Ross et al. 2017:119). These changes then beg the question of how data analytic ‘decision support systems’ are being implemented and how they are guiding management decisions. For example, are they creating ‘machine-driven data management bureaucracy and control’ or are they empowering health workers to make better ‘evidence based’ decisions rather than relying on ‘gut instinct’? (McAfee & Brynjolfsson, 2012; Pedersen & Aagaard, 2015; Ross et al. 2017: 114-116). If it is the former then the decision making ‘support’ system may simply be transformed into top down decision making and control approach, which is unlikely to be welcomed by experienced health professionals. If it is the latter, then staff are more likely to take psychological ownership of the new system (Paré et al. 2006).

Data-analytic supported decision making further raises questions on the underlying metrics that are guiding decision making processes? (O’Neil 2016; Ross et al. 2017). Put simply, what’s in the black box? This suggests the need for transparency in the implementation of data-analytic supported eHealth systems and associated new processes. The extent to which human cognitive processes and decisions are being influenced or even replaced by prescriptive data analytics (Chen et al., 2012; Ross et al. 2017:121), is also a particular issue in a health sector context where clinical decisions, that have traditionally been based on clinician knowledge and experience, directly impact on patient health outcomes. Therefore, while the pace of ICT advances makes the continued uptake of these new technologies across the health sector inevitable (and in many areas increasingly essential), we should also take note of Mortensen et al. (2015) who caution that “data analytics should... be seen as a tool rather than a solution in itself” (Mortensen, Doherty, & Robinson, 2015).

The following case study provides an example of how a health sector agency has had to deal with many of the above implementation challenges in an innovative Australian Public Health sector initiative entitled, the ‘Choosing Wisely Pathology’ project.

Choosing Wisely Pathology

Background

Gold Coast Health is situated in a large regional city in Queensland, Australia. Here we analyse how Gold Coast Health implemented a data-analytic supported eHealth project that reviewed the ordering of pathology tests in a large public hospital. The case study discussion and analysis identifies the drivers for these workplace changes, the context within which they were made and the mechanisms of change (Nancarrow et al. (2013).

In relation to change management drivers, John Kotter (1996) observed that the ‘burning platform and urgency’ for activating a project is often multi-layered. In this regard, at the national level, public pathology workloads across Australia were increasing annually by 5 to 10 per cent (NCPP 2011). At the local level, the Gold Coast region is one of the fastest growing areas, in terms of population, in Australia (GCCEC 2018). Gold Coast Health was therefore being challenged through increasing patient activity at the front door, yet needing to work within budgetary constraints and cost pressures when meeting that demand. With more patients accessing the health service, similar 5 to 10 per cent annual increases in public pathology testing were being experienced, both in test volumes and expenditure.

It was reasonable to infer that the increases in pathology test ordering at Gold Coast Health simply reflected the above concurrent growth in patient numbers and activity. After all, that was the national trend. However, there was a belief within some clinical circles at Gold Coast Health that something more could be done to address this issue. Questions were therefore posed in relation to whether patients were getting the right tests at the right time in their care pathway. Were clinicians, for instance, ordering tests to help diagnose and treat patients, or were they ordering based on routine or fear of missing something?

The fear factor appeared to be a particularly strong motivator for junior medical officers ordering tests, which was likely related to their relative lack of experience and clinical specialisation in comparison to their senior medical officer colleagues. Junior doctors may also be required to make diagnoses and treatment decisions without direct supervision from senior doctors, which in turn can perpetuate a culture of ordering tests ‘just in case’ they are required. Senior doctors were also sometimes unaware that tests had been ordered, and

therefore the test results were not reviewed. Such tests then became a waste of pathology time and resources.

Another consideration was the value of ordering certain tests and their timing in the patient pathway. Should the test, for example, be ordered on the first day of patient admission, and any subsequent days thereafter, or should other clinical observations be used instead? Are guidelines and processes in place to help inform clinicians what to order? Was there consistency in pathology ordering? Within specialty teams and service areas, for example, were there particular clinicians who had testing preferences, or was there a more universal approach to testing? Further, what data was available to measure and monitor pathology ordering behaviour?

Around the same time that Gold Coast Health was pondering these questions, NPS MedicineWise (an independent not for profit Australian health sector organisation) launched the Choosing Wisely Australia Initiative. Part of an international movement, Choosing Wisely Australia was promoting promotes an ‘important conversations about unnecessary tests, treatments and procedures’ (CWA 2016). This led to NPS Medicine Wise establishing the ‘Choosing Wisely Australia’ initiative in 2015, which included leadership from medical colleges, societies and associations that sort seek to challenge the way organisations consumers and health professionals think about healthcare and question the notion that ‘more is always better’ (CWA 2016). Recognising the need to review the appropriate use of healthcare tests and provide better value care for patients, Gold Coast Health then partnered with ‘Choosing Wisely Australia’ and initiated the ‘Choosing Wisely Pathology’ Project.

Data Approach

The Choosing Wisely Pathology’ initiative was led and sponsored by a service and a clinical director, who envisaged the potential benefits of this new approach. The early activation of a Working Group to oversee the successful implementation of the project also helped to secure senior management support. This included providing resources to establish a small project team to review pathology ordering behaviour through an informatics lens. A two-person project team was therefore commissioned in early 2016 to manage improve the quality use of pathology testing at Gold Coast Health.

One of the first tasks faced by the project team was to assess the current state of pathology ordering, including how these tests were being utilised by individual specialty and service areas. Given the multitude of clinical data being collected at the health service this was a serious challenge. The project team, however, were able to develop a robust dataset from which to host further analysis. Importantly, the project team did not take a traditional transactional data approach, which would only have described the overall number and type of pathology tests being ordered by clinicians (i.e. an aggregated data approach). Rather, they instead created a rich dataset using a clinical costing system that matched pathology tests with patient encounters (i.e. individualised patient data approach). By allocating all costs directly to individual patient episodes the clinical costing system then provided far more accurate cost allocation information at the patient level. This clinical costing data proved very useful as it revealed all the inputs and outputs attributed to a patient, including pathology tests ordered.

Using clinical costing data to review pathology ordering behaviour further allowed Gold Coast Health clinicians to ‘visualise’ pathology testing patterns, as patients moved through the health service. Instead of viewing only pathology transactions, the project dataset revealed additional metrics, such as, the clinical specialty of care under which the patient was at the time of testing. For example, the Respiratory team may order daily blood tests to check medicine toxicity levels for a patient. The clinical costing data then matches all the other activities happening for the patient, including any other pathology tests ordered in combination (for example, sputum tests), the final diagnosis when the patient was discharged from care (for example, asthma), plus any other interactions the patients may have had with the health service during their stay. This data then tells a story about what is happening with the patient around the pathology ordering event. This in turn provides more context for clinicians when they are reviewing the case and deciding whether the pathology tests were appropriate or required.

To encourage sustainability beyond the life of the project, an interactive and dynamic dashboard was developed so clinicians could continue to review pathology ordering data. The dashboard provides visibility for clinicians about the pathology ordering practices across the patient flow and within specific specialties. It further promotes clinical enquiry and review to determine if tests are appropriate for managing patient diagnosis and treatment. Accessing the dashboard, for example, allows clinicians to view patient tests, clinical specialties, time periods, retests, ordering details and volumes. In regards to the latter, once an intervention is

activated, clinicians can view and analyse changes in test volumes to better understand if the intervention is working as intended.

This is powerful information which allows clinicians to discover and identify key tests to target for intervention, implement real actions to improve quality and safety, reduce unnecessary testing, and reduce variation in care. The dashboard implementation process further accorded with the recommendations of the data analytics literature by providing a transparent approach in relation to how the data was being analysed (O'Neil 2016; Ross et al. 2017), along with a bottom up decision making approach on the part of the clinical end users in relation to how they used the data to support their decision making processes (Pedersen & Aagaard 2015; Ross 2015). The subsequent uptake of the dashboard amongst clinicians also suggests that they found the information useful and relatively easy to use (see Paré et al. 2006).

Clinical Leadership & Collaboration

The project team used a collaborative approach that included all key stakeholders (see also Hawley et al.; Knight et al., 2014). Once the project team had researched and understood pathology utilisation within a specialty, for example, they worked with the relevant lead clinicians and pathology experts to determine the clinical appropriateness of the pathology ordering patterns.

This process included activating clinical working groups within each specialty to have conversations about pathology ordering behaviour. These working groups were made up of lead medical, nursing, pathology, and business representatives. Using the Haematology service as an example, working group invitations would be shared with the medical director, staff specialists (senior doctors), nursing leads of the wards/day units, allied health leads, quality and safety representatives, business representatives, and any relevant pathology stakeholders (for example, microbiology representation). This allowed input and collaboration from different healthcare services stake holders, who may have quite different opinions and goals (Kilbourne et al. 2010; Popay et al. 1998). Once all the key players were around the table, the project team created a profile of pathology use to start the conversation about the appropriateness of the ordering behaviour.

Clinical engagement and leadership was absolutely vital to this process, as it empowered clinicians examine what pathology tests were ordered on the floor and in the wards. This

allowed them to understand the interactions that were occurring throughout the ‘entire’ patient flow, a complex and multi-faceted process, rather than just one particular part of a patient’s journey. For example, clinicians could now see the pathology tests that occurred when a patient first arrived at the emergency department, were admitted to a short stay area, moved into a longer stay inpatient ward, went to surgery, and post-discharged to an outpatient clinic.

The clinical teams targeted key tests they wanted to review, and came up with ideas to manage the change in ordering behaviour within their teams. This approach then empowered the clinical teams to create their own solutions and initiatives based on the data. As such, the clinical teams were not told what changes to make (Pedersen & Aagaard 2015). Rather they took ownership of the process, which in turn helped to ‘embed’ cultural change in relation to pathology test ordering. Examples of the changes introduced by clinical teams included:

- development of clinical guidelines and pathways to standardise pathology ordering practices;
- completion of clinical audits and practice reviews to check behaviour;
- influencing education, orientation, handover and training processes within their specialty to include choosing wisely messaging;
- conducting performance analysis and benchmarking using the dashboard tools; and
- undertaking research and evaluation to match ordering behaviour with contemporary clinical standards.

Once these demand management strategies were implemented, the project team helped to monitor and provide ongoing reports regarding perceived benefits and/or any other issues related to the project, to ensure long-term sustainability of these change to pathology ordering processes.

Implementation Challenges

There were a number of challenges in implementing the Choosing Wisely Pathology Project. For example, there appeared to be an initial belief amongst some stakeholders that hospital speciality areas that traditionally ordered a relatively high number of pathology tests were being targeted, because they could provide ‘low hanging fruit’ that would allow the project to gain some ‘quick wins’ in relation to changing ordering behaviour.

For some specialty areas, this scenario may have at first appeared true, as the high volume of pathology ordering meant that any decrease was exponentially noticed. The most significant on-going changes to pathology ordering behaviour, however, did not come from any ‘quick wins’. Rather, it came from the substantial time that clinicians invested in collaborative discussions that allowed them to use the data to develop policies and provide recommendations/directives to team members about when to order tests.

Perhaps not surprisingly, there was also some initial scepticism from senior medical officers in some specialties about the motivation behind the project, fearing that it was a budget recovery or cost-cutting exercise. These fears, however, were ameliorated once it was realised that the project team were not engaging in a top down data driven decision making approach. Rather, the project team were able to show that this was a ‘bottom up’ collaborative approach, whereby their role was to present data on pathology utilisation within a speciality, from which the clinicians themselves could then identify tests to target for intervention. In this regard, the project team saw their role as ‘enablers’ of change (i.e. not telling clinicians how to change their behaviour).

Once staff became more open and accepting of the motivations behind the project, the next layer of cynicism came from people who refuted the pathology utilisation data that was presented to them. This included people using terms such as ‘the data is wrong!’. The drill through capability within the dashboard was a valuable feature in winning over doubters, as it provided evidence that the tests being presented were ordered by doctors within the speciality. This included the dashboard’s ability to go down to the granular test level to display the requesting doctor details.

A further challenge related to the busy schedule of medical and nursing professionals, which impacted on their availability to review pathology ordering changes. This required regular check-ins from project team members to monitor progress.

Speciality Case Study: Adult Intensive Care Unit

The actions and strategies of the Adult Intensive Care Unit (Adult ICU) provide a good example of how teams were empowered to develop their own strategies in relation to the implementation of the Choosing Wisely Pathology project.

Interestingly, the project team were initially unsuccessful when they first attempted to present pathology utilisation data to the Adult ICU medical leadership team. This was mainly due to competing priorities and focus for the critical care team. It should be noted that tertiary intensive care services, such as the Adult ICU, support the most complex and ‘sickest’ patients and operate in extremely busy and intense environments. It could therefore be expected that critical care teams would be very concerned about the potential impacts that any changes to pathology testing practices may have on the health of critically ill patients and at the same time have limited time to consider these new approaches.

Despite this early pushback, a group of clinicians and lead nurses within Adult ICU started challenging their own norms around pathology ordering behaviour. They were motivated in part to review their pathology ordering practices in order to better understand how their current approaches were impacting on their most critically ill patients. This led to the intensive care team mobilising their own Choosing Wisely Pathology working group, which collaboratively developed key tests of focus. The group further encouraged cultural change through repeat messaging at structured education sessions and safety huddles, and when handing over patients to incoming shifts.

Due to the critical nature of patients in Adult ICU, nursing staff are dedicated to a single patient for their whole shift. This presents challenges in relation to Adult ICU staff participating in team conversations and/or accessing refresher materials. To deal with this situation, the staff developed prompt cards for placing at bedsides, as a visual reminder about their tests of focus and agreed intervention strategies (see Figure 1).

Figure 1: Prompt card example: Blood Gas Tests

Source: A prompt card introduced into the Adult ICU unit.

The graph outlined in Figure 2 provides an example of Blood Gas testing from July 2016 to June 2018. It shows a reduction in blood gases ordered by the Intensive Care team from April 2017 onwards. This included a significant reduction in routine tests that were conducted early in the morning. By graphing the timing of blood gas tests by the hour of day, it was observed that the period between 4.00 a.m. and 6.00 a.m. showed a significant spike in testing. This practice was a legacy from when blood analysers were not available at the point of care. Tests were therefore run early in the morning and sent to the lab so that when the medical rounds moved through the intensive care unit, the blood workup was completed for the medical team's review.

Figure 2: Choosing Wisely Pathology Dashboard

Source: Excerpt from Choosing Wisely Pathology Dashboard created by Gold Coast Health

Blood gas analysers however are now more sophisticated and are co-located within Adult ICU. This means that the results can now be produced on-site and almost on demand. If a doctor wants to check the blood gas levels of a critical patient, they can therefore order it on the spot and have the results almost immediately. However, while the technology had changed, behavioural changes in relation to blood gas testing had not. With the dashboard telling a story about this ordering behaviour, the Adult ICU team ceased ordering these routine blood gases based on the time of day. Instead they began ordering these tests based on patient condition and indications.

The results over the following 15-month period highlighted the benefits of reducing the frequency of this single test in Adult ICU, including:

- 39 per cent reduction of blood gas testing between 4.00 a.m. and 6.00 a.m.;
- No adverse outcomes for patients as monitored via clinical audit;
- Average monthly ordering reduced from 495 to 300 blood gases per month; and
- Estimated saving of \$32,000 for this single test.

The Adult ICU therefore provides evidence of data analytics facilitating positive behavioural changes leading to more effective patient outcomes. Importantly, changes to processes and behaviours were developed and implemented via a collaborative process within the Adult ICU.

Benefits and Sustained Change

Central to the whole Choosing Wisely Pathology project strategy was the desire to improve patient safety and experience. Some patient pathology tests can also be quite invasive. The benefits have therefore been realised by ensuring patients do not have unnecessary or inappropriate tests, which in turn reduces their exposure to undue risk of harm and emotional stress. This emphasis on improving pathology testing quality and safety, along with education on better practices, further enhances the value of pathology services.

The project also created associated ongoing behavioural benefits, including greater collaboration between stakeholders. The education and learning values gained through the project, for example, have allowed clinicians to keep up-to-date with contemporary clinical standards by working closely with the medical colleges and societies, and their

recommendations. These behavioural changes have further fostered a learning organisation approach to resolving matters (Senge 1996).

The data and business intelligence tools and enhanced collaborative behaviours developed during the Choosing Wisely Pathology project therefore resulted in sustained clinical practice improvements in pathology ordering behaviour at Gold Coast Health. This included greater allocative efficiencies, with testing being focused on areas of greatest need. In this regard, the number of some pathology tests increased while others decreased depending on the evidence of the efficacy of these tests in terms of patient welfare. New approaches and processes were then based on the team enabling the development of more ‘effective’ pathology testing, rather than more ‘efficient’ pathology testing per se. This resulted in a reduction in the ordering of routine and repeat pathology tests, while the overall number of tests being ordered also decreased despite higher than predicted patient activity growth.

As outlined above, the change management approach with clinicians was framed by promoting wise choices and avoiding patients having to undergo unnecessary tests. Any cost reductions have therefore been a positive externality of this project, which in turn allows more patients to be treated. Prior to the introduction of the Choosing Wisely program, pathology test volumes were increasing with patient activity growth. Basically, as more patients accessed the health service, more tests were being ordered. With clinicians making wiser ordering decisions, supported by informatics, this trend has been broken. This aligns with the ethos of helping the health dollar go further in times of increasing activity and resource use, whilst improving quality and safety for patients through the reduction of unnecessary testing.

Conclusion

The increasing adoption of eHealth systems, facilitated by rapid advances in eHealth technologies, has been driven by health sector stakeholder requirements. This includes public health sectors across industrialised countries, including Australia, facing the challenges of rising health costs and finite health budgets. Trying to stretch health budgets further, however, is a difficult balancing act in relation to reducing costs without negatively impacting on patient health care outcomes (see Figure 1). New technologies, including health data analytics, offer much promise in relation to these issues, including from clinical and administrative

perspectives. However, they also create their own issues, including data privacy and data driven bureaucracy challenges.

In reviewing the literature and the above case study, two key themes recur and underpin many of the conclusions and recommendations in relation to the successful implementation and on-going adoption of eHealth systems; collaboration and participation. These concepts are of particular importance to the health sector, which by its nature, is composed of disparate stakeholder groups, who may have differing aims, goals and requirements. Further, the health sector comprises highly educated and skilled health professionals who are unlikely to accept top down directives that potentially impact on patient health care. This points to the need to develop participatory and collaborative eHealth systems in the 21st century. Traditional top-down approaches of healthcare service designs therefore need to be replaced by co-designed systems, as all stakeholder inputs are necessary for organisations to achieve the best possible outcomes, processes and structures (Braithwaite et al., 2016).

In this regard, the Choosing Wisely Pathology project case study provides an interesting example of how a data-analytic-supported eHealth system can be successfully implemented by empowering health staff, including clinicians, to take ownership of the process. This included the project being adopted by staff within an Adult ICU unit, who operate in an extremely intense and challenging health environments. Data analytics in this case were used as a clinical tool, not a management directive. Further, any cost reductions linked to the Choosing Wisely Pathology project were linked to more effective uses of pathology resources, in terms of greater allocative efficiencies, as opposed any simple reductions in testing. In terms of the Donabedian framework (see Figure 1) the project therefore led to improved staff, process and patient health care outcomes. It is also important not to view the Choosing Wisely Pathology project in isolation. Rather, the project is operating within the broader context of the rapid changes occurring in the e-health and m-health sphere, with continued learning along the way.

The literature and the case study therefore aim to provide knowledge and recommendations that may hopefully assist health sector organisations to develop goals and implementation strategies in relation to data-analytic supported eHealth systems. These, are important considerations given the increasing role that eHealth systems will continue to play in health sectors across industrialised countries, including Australia, as public health sectors seek to find better ways to deal with the challenges of increasing patient workloads and finite resources.

The size, complexity and varied needs of the health sector also points to the need for more empirical research into this area.

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Appendix 1: Historical eHealth themes

No	Authors & Year	Identified emerging theme
1	Popay, Rogers & Williams (1998) -(historic reference)	Implications for Health Service Research are not clearly defined. Further studies are required for devising appropriate research for effective policy and practice impact.
2	Ford, Menachemi, and Phillips (2006) - (historic reference)	Reluctant adoption of EHR/EMR by clinicians. Authors predicted that it is unlikely to meet targets of universal EHR within the time-frame targeted by the policymakers.
3	Paré, Sicotte, and Jacques (2006) - (historic reference)	Psychological ownership is a significant factor in physician's acceptance of eHealth. 'Perceived usefulness' and 'perceived ease of use' determine the participation level and strength of belief in these systems.
4	Mechanic, (2008) - (historic reference)	Rethinking of the medical professionalism suggested in the context of EHR systems. Realisation that technology and IT will be important as tools 'adjunct to medical professionalism' and the adoption of the technology will become inevitable.
5	Black et al., (2011)	Discussion on claimed v/s actual benefits of the EHR implementation begins. Identified gap between the postulated and demonstrated benefits of eHealth implementations
6	Holroyd-Leduc et al., (2011)	EHR/EMR benefits on the health outcomes found to be unclear. Authors find that these systems have positive impact on the structures and the process in healthcare. Donabedian's framework is applicable.
7	Lieu, and Cho (2011)	Differing perceptions of public on eHealth systems studied. Willingness to pay for the eHealth program in public systems appears to depend on the perceived benefits and 'popular perceptions'.
8	Smith et al., (2011) - (Australian study)	Authors find that to achieve intended service quality in health, appropriate recognition and support of clinical informatics staff is necessary. Teething problems of adoption of eHealth appear.
9	Boruff, and Bilodeau (2012)	Millennials have better perception of eHealth technology. Medical students are satisfied with the web-based mobile access to subject guide. Internet access to library remains an issue as an infrastructure issue.
10	Hall et al., (2012)	Databases and data analytics provide the capacity to achieve results faster, cost-effectively and with fewer biases in pharmacoepidemiological research. Emergence of large

		scale aggregated data processing and analytics applications in health.
11	McGinn et al., (2012)	Aggregated data from healthcare systems is increasingly used for analytics. Users have complex perspectives on the eHealth. Larger population study is required for better understanding of the perspectives.
12	Demirkan, and Delen (2013)	Large scale aggregated health data can be processed quickly using cloud based big data analytics to bring down costs, and to improve quality & efficiency in healthcare.
13	Knight, et al. (2014)	Quality improvement collaborative (QIC) concept is tested. The 'data-quality' is identified as a major problem. Sharing health summaries between GP practices and patients allows successful collaboration.
14	Erekson, and Iglesia, (2015)	Big data capable open access registries and decision support systems for eHealth systems allow abstraction and meaningful use. Ability to access such aggregated data accurately, meaningfully and on-time enhances quality decision support.
15	Van Poucke et al., (2016)	Innovative data visualisation technology can extract data, seamlessly work on it, process and apply predictive analytics in near-real-time. This capability can provide the cutting edge predictive data analytics tools to the health and clinical experts.